AI-BASED REMAINING USEFUL LIFE PREDICTION AND MODELLING OF SEAWATER DESALINATION MEMBRANES

by

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Declaration of Authorship

I declare that this thesis is my own work and, to the best of my knowledge and belief, it does not contain material published or written by a third party, except where permission has been obtained and/or appropriately cited through full and accurate referencing.

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Dedication

This thesis is dedicated to my loving family, whose unwavering support, encouragement, and understanding have been the cornerstone of my academic journey. Their endless love and belief in my abilities have been a constant source of inspiration and motivation.

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Abstract

The increasing demand for freshwater has heightened the reliance on desalination plants as a vital resource, particularly in the context of the Sharjah Electricity, Water and Gas Authority (SEWA) in the United Arab Emirates (UAE), which integrates different water desalination plants, including reverse osmosis (RO) to produce water. This thesis focuses on the development of an artificial intelligence-based predictive model for estimating the remaining useful life (RUL) of RO membranes. It addresses the critical operational challenge of membrane fouling caused by particle accumulation, which can lead to significant efficiency losses and system damage. The concept of RUL is defined as the anticipated time until the RO membrane reaches a specified performance threshold, guiding maintenance actions to enhance system longevity and efficiency. The predictive model developed in this study utilizes data from SEWA's operational database and laboratory records to forecast the RUL. R Software was employed as the primary tool for building and testing the predictive models, including Linear Regression, Decision Tree, Random Forest, and XGBoost. The Random Forest algorithm demonstrated the best performance, achieving an R^2 coefficient of 0.984, an RMSE of 0.136, and an MAE of 0.0997. These results highlight the exceptional accuracy and reliability of the model in predicting the RUL. Additionally, the findings from the variable importance analysis revealed that the most significant features influencing the RUL were SDI, water temperature, pump speed, and the age of the membrane. Understanding these key variables can provide valuable insights into optimizing operational conditions, thus extending membrane lifespan. By accurately predicting RUL, the model aims to reduce pressure changes that contribute to fouling and mitigate potential membrane damage. The implementation of this AI-driven model is expected to optimize clean-in-place (CIP) scheduling, ultimately maximizing the longevity and performance of RO membranes. The findings of this research will not only enhance understanding of the necessary operating conditions for effective seawater treatment but will also contribute to the broader literature on predictive maintenance in desalination, supporting more efficient and sustainable water production practices.

Keywords: Reverse Osmosis, Membranes fouling, Predictive Modelling, Remaining Useful Life (RUL), Clean-in-Place, Desalination

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List of Abbreviations

AI	Artificial Intelligence
ANNs	Artificial Neural Networks
CIP	Clean-in-Place
C-MAPSS	Commercial Modular Aerospace Propulsion System Simulation
DAF	Dissolved Air Flotation
DTs	Decision Trees
EDA	Exploratory Data Analysis
LSTM	Long Shor-term Memory
MAE	Mean Absolute Error
MED	Multi-effect Distillation
MSF	Multi-stage Flash
ML	Machine Learning
RMSE	Root Mean Squared Error
RF	Random Forests
RO	Reverse Osmosis
RS	R-squared
RUL	Remaining Useful Life
SEWA	Sharjah Electricity, Water and Gas Authority
SDI	Silt Density Index
SVM	Support Vector Machines
UAE	United Arab Emirates

Chapter 1. Introduction

1.1 Overview

This chapter provides background information that is crucial in understanding the significance of the proposed research, namely building predictive modelling. First, this part presents a background on the importance of conventional and current desalination technologies to generate electricity and treat seawater. Information on the Sharjah Electricity, Water and Gas Authority (SEWA) in the UAE on regulating desalinated water is provided. Next, the fundamental contribution of the RO membrane-based system applied in desalination plants is discussed. Moreover, the chapter emphasizes the effect and significance of RO membrane performance in terms of longevity. Overall, the background provides a comprehensive framework and context to formulate the problem statement and establish the aims and objectives of the research proposal.

1.2 Background

2. *Desalination overview*:

   The increasing population is an issue that has put significant pressure on accessing and using clean water. The unreliability of the natural resources providing fresh water because of the overuse of water resources and human contamination has exacerbated this problem. The UAE experiences the issue as well. According to Alaa et al. [1] apart from the UAE's water scarcity and contamination, the region has relied heavily on non-conventional resources [1]. Desalination plays a crucial role in addressing freshwater scarcity by providing an essential source of water through water treatment plants, especially in regions with inadequate natural water resources. Electricity demand in the Gulf Cooperation Council (GCC) countries, including the UAE, is driven by sectors like water desalination, air-conditioning, and lighting. While fossil fuels currently dominate power generation, efforts are underway to transition to cleaner energy sources like renewables. Seawater desalination, a critical process for meeting water needs, contributes significantly to electricity consumption, especially with rising demand. This study [2] explores the feasibility of meeting over 20% of electricity demand in Ajman, UAE, through wind energy, particularly for powering desalination and lighting systems. A rise in the consumption of water resources has made treatment and management strategies crucial in the UAE to meet water demand among its population. Water resources in

the UAE comprise both conventional and non-conventional resources, as well as desalinated water, as shown in Figure. 1 [3]. The motivation behind increasing desalination capacity is explained by seawater availability and attractive tactics to meet water demand at a favourable cost since industries have shown willingness and ability to establish plants that utilize technologies to address the freshwater scarcity issue. Since the early 1970s, the UAE has made extending non-conventional water resource management to bridge the gap between resources and population demand a normal practice [4]. Thus, the UAE must maintain the ability to establish desalination plants and guarantee their resilience for water productivity and electricity generation.

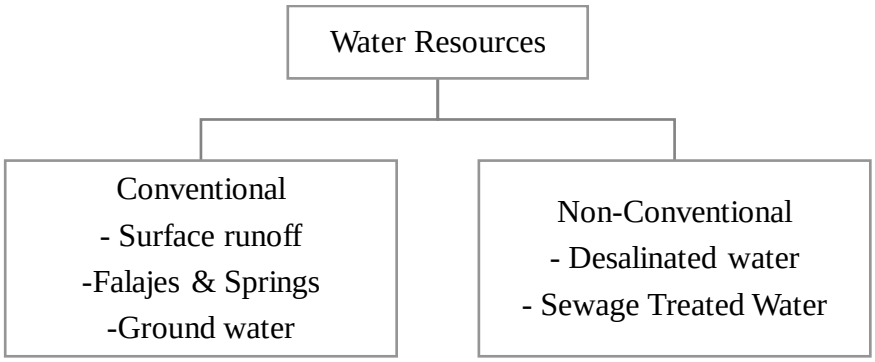

Figure 1. Water resources in the UAE [3].

3. *SEWA and desalination*:

The SEWA power station in the UAE is a typical example of a project for increasing desalinated water production. The strategy is vital to sustain water provision for modern and future generations. Its main undertaking is supplying the UAE with freshwater from desalinated and underground resources using modern industrial techniques to facilitate water transmission and distribution networks to consumers [3]. Thus, SEWA has become a supportive plant to source fresh water for industrial and residential purposes. It is essential that Sharjah Municipality has spearheaded efforts in underground water treatment. In 2012, it allocated AED 227 million to cater to the operations of sewerage treatment in Al Sajaa area, which included increasing the capacity to produce 50,000 m^3 compared to the previous result of 30,000 m^3/day [5]. Accordingly, SEWA utilizes a model meant to optimize the

water treatment plan for clean water usage and energy generation. Its sustainability measures are meant for desalination to ensure the ability to increase and sustain these operations. Moreover, the significance of this development can be understood from the outlook of the increase in the number of operating desalination plants. In 2008, the UAE had 18 facilities that applied desalination methods as a preferred method to increase the alternative approaches to the existing conventional desalination processes [6]. It is SEWA's continued engagement in applying desalination methods that suggests that increasing the quality of water production and electricity generation is essential once the efficiency and capacity of the systems in the power station are ensured.

4. *SEWA and membrane-based system*:

The plant uses an RO process for water desalination and electricity generation. The significance of this procedure, especially through RO membrane, cannot be overemphasized since it has become a preferred method for desalination for its lower energy requirements [6]. Moreover, this advantage could be understood considering the reduced time spent. Additionally, RO is favoured for desalination due to its energy efficiency, scalability, high salt rejection, and versatility in removing contaminants. Continuous technological advancements further enhance its appeal as a preferred method for producing clean and safe drinking water from various sources. The RO pre-treatment process is an integrated technology that allows simultaneous water treatment and the production of electricity in reduced time and minimized energy consumption [6]. The description pinpoints the significance of promoting the performance of RO membrane to prevent it from potential damage. The significance of promoting the performance of RO membranes lies in mitigating potential damage, particularly fouling, which can significantly impair their efficiency and lifespan. Addressing fouling issues is crucial for ensuring optimal operation and longevity of the membrane system. Further, the evidence suggests that RO membrane is the preferred technology in the UAE due to its effectiveness in desalinating water efficiently and successfully [7]. The preference for RO membrane technology in the UAE is largely attributed to its effectiveness in efficiently desalinating water while meeting stringent purity standards and minimizing energy requirements. This technology offers a cost-effective and sustainable solution for addressing water scarcity challenges in the

region. Thus, the inclination to maximize its utilization at SEWA is vital since the plant has a CIP procedure, which is a cleaning procedure for the membranes in the RO. In the principle underpinning the membrane process, the condition involved is the selective passage of particles. The process is pressure-driven, hence requiring controlling the accumulation of particles to enforce their transportation via the membranes against the potential chemical gradient [8]. Figure. 2 shows a typical RO system. A typical (RO) system comprises several key components: a pre-filter, a semipermeable membrane, a pressurization mechanism, a post-filter, and a storage tank. The process begins as water flows through the pre-filter, removing sediments, chlorine, and other contaminants. Then, pressurized water is forced through the semipermeable membrane, where only pure water molecules can pass through, leaving behind impurities. These impurities are diverted to the drain, while the purified water continues to the post-filter, which removes any remaining tastes or odours. Finally, the clean water is stored in a tank until it's needed. This method ensures efficient removal of contaminants, providing safe and clean drinking water for various applications. The opportunities for desalinated water reuse should accompany efficiency in CIP optimization and scheduling. Moreover, the SEWA plant should demonstrate value in terms of cost-effectiveness to meet user-end needs [9]. Thus, the RO membrane system should align with reliable CIP procedures to prevent damaging their forms. Research can assess strategies to limit the accumulation of particles that lead to clogging. Thus, building predictive modelling is a practical solution to this problem since SEWA does not have an effective model to predict pressure increase while using CIP.

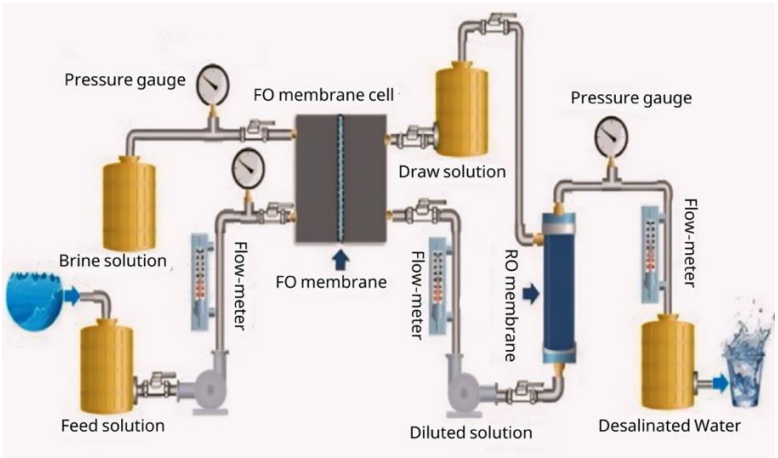

Figure 2. A typical integrated RO integrated system [10].

1.3 Problem Statement

SEWA in the UAE integrates conventional and advanced water desalination technologies evident in RO, multi-stage flash (MSF), and multi-effect distillation (MED). As a vital commercial plant involved in generating electricity and water, maintaining the efficiency of the membranes in the RO is essential considering that the CIP procedure should be optimized to avoid the accumulation of particles, which causes clogging. The problem of the proposed research is demonstrated in the complexity of CIP scheduling and optimization when the pressure change in the membrane increases, hence not allowing it to rise higher since it will damage the RO membranes since their sensitivity should not be compromised. Thus, to explore and evaluate various artificial intelligence (AI) models to construct a robust predictive framework, aimed at enhancing the efficiency of membrane maintenance through CIP actions. Moreover, the selection of Remaining Useful Life as the focus of the proposed research stems from its critical role in optimizing membrane maintenance. By accurately predicting the RUL of RO membranes, proactive maintenance strategies can be implemented, ensuring prolonged operational lifespan and mitigating the risk of unexpected failures. Therefore, the purpose of the proposed research is to build a prediction model of the RO membrane RUL to optimize for the membrane maintenance through CIP actions.

1.4 Aims and Objectives

The proposed research will be based on two major aims:

1) to build an AI based prediction model for the RO membrane RUL;

2) To evaluate various predictive algorithms and identify the most effective model for accurate and reliable predictions;

The requirement for increasing the performance of SEWA plants in its RO unit is necessary for performance and efficiency. Therefore, the basis of this study is to guarantee that CIP protocols align with the rise in the membrane's lifespan extension. The objectives to accomplish the aims are outlined as follows:

1. To explore the literature on RO membrane fouling and CIP procedures;
2. To assess the impact of CIP system enhancement on mitigating RO membrane damage and improving its overall efficiency;

3. To collect data and lab results from SEWA's RO unit and build predictive modelling for the RUL;
4. To examine and validate the efficiency of the build AI-based life predictive modelling of seawater desalination for RUL of the membranes.

Chapter 2. Background and Literature Review

This chapter presents existing empirical evidence about RO membrane fouling and optimization of CIP procedures. Additionally, it examines the impact of enhancing the CIP system to moderate membrane damage to boost its overall efficiency and manage the accumulation of particles and resulting clogging. The themes that facilitate accomplishing these objectives include RO membrane fouling, RO maintenance practices, and remaining useful life predictive modelling. Overall, the concepts are complementary since they assist in identifying and addressing the research problem involving seawater desalination RO membranes.

2.1 RO Membrane Fouling

Membrane-based technologies in water desalination are promising technologies but fouling limits their efficiency in improving the separation process. According to [11], fouling is the "deposition and accumulation of undesired materials on the surface of or inside a given host material such as membranes, heat exchangers, and boilers". From this perspective, it is vital that membrane-based processes integrate complexity in terms of chemical reactions since the surface of the membrane and the feed elements limit the operation's efficiency of the system. The problem becomes complicated during the desalination process. The general lifespan of RO membranes typically lasts between 2 to 7 years. However, with proper maintenance and under ideal conditions, some membranes can last up to 10 years or more [11]. Results from the study done by Eltanbouly et al., present a data-driven approach to predict the RUL of the membrane, hence identifying fouling as a reason that reduces the system's safety threshold [12]. The membrane cleaning procedure can hinder its output, which is attributed to the distorted operating conditions. The immediate outcome of disrupted membrane plant operation is shortened membrane life [12]. A solution to addressing this issue has been proposed in the form of anti-fouling surface-patterned membranes. In this context, the study by Ibrahim and Hilal, investigated the suitability of the surface-patterned membranes to improve the spacer-assisted filtration process and used diamond- and honeycomb-fabricated surface-patterned membranes [13]. The results reveal that the membranes are effective during the filtration process compared to the conventional feed spacer-assisted filtration in terms of higher permeability and anti-fouling operations.

These findings affirm that the configuration of a membrane system remains a crucial factor in its performance based on the employed fabrication technique.

Evidence suggests that the lifespan of the RO membrane possesses antifouling and material properties that forecast the filtration cycle pattern. As shown in [14], the desalination performance of RO membranes can be improved by using nano reinforcing materials since they show great suitability when synthesized in the preparation of nanocomposite aromatic polyamide and crystalline cellulose nanofiber membranes with the potential for a longer lifespan, thus guaranteeing antifouling resistance. The utilization of nano reinforcing materials enhances the desalination performance of RO membranes by augmenting their structural integrity and surface properties. This improvement is achieved through the incorporation of nanocomposite aromatic polyamide and crystalline cellulose nanofiber membranes, which exhibit increased durability and resistance to fouling, thereby ensuring prolonged membrane lifespan and sustained antifouling capabilities. Different methods of intensifying the performance of RO membranes indicate that a combination of factors increases the implementation of this desalination technique. Similarly, in the assessment of various processes to increase the useful life and reuse of the RO membrane elements, it is determined that different components are integrated with the physical fouling to boost the technical and operational features of the system in its life cycle [15]. The research trends on the proper selection of materials for desalination plants underscore the relationship between corrosion resistance and the smooth operations of desalination industries. A literature analysis of desalination trends identified that RO (27%) is the most explored desalination technique when compared to renewable energy desalination (26%), thermal desalination (14%), brine (14%), electrodialysis (8%), and membrane distillation (7%) [16]. The higher proportion of RO is associated with the vital consideration of desalination plants in choosing materials that improve the opportunity to address the water salinity problem.

Existing academic literature reviews the parameters and contexts leading to the accumulation of particles in the RO membrane, thus hindering its efficiency and longevity. A review [17] explained the main factors contributing to the formation and development of particles and biological foulants and outlined suitable mitigation strategies to address RO membrane fouling. Its foundation is guided by the fact that

fouling caused by physiochemical reactions between membrane materials and water pollutants leads to the build-up of particles in the membrane surface or pores, lowering the efficiency of RO membranes. Similarly, a state-of-the-art review [18] identified the parameters of the flux decline, increased feed pressure, and varied fouling types (biological fouling and organic fouling) to curtail the operations of the RO membrane system. The analysis provides a comprehensive conclusion about the improvements in brine management and developing membranes integrating chlorine resistance and specific contaminants. Furthermore, crucial factors behind the accumulation of particles include cleaning protocols, feed water quality, operating conditions, and membrane characteristics [18]. Moreover, another review analyzed relevant literature concerning the usage of artificial neural networks focusing on the application of AI-based fouling prediction models to improve membrane fouling forecast [19]. In the paper, it is determined that artificial neural networks have great potential to optimize membrane-based procedures since they identify the underlying complex chemical reactions and physical processes in membrane fouling. Consequently, one should develop an adequate awareness of the desalination maintenance practices that complement reducing membrane fouling to increase the life usefulness of the RO membrane's system.

2.2 RO Membrane Maintenance Practices

The maintenance practices of the RO membrane system revolve around CIP procedures. The technique is explained as an automated cleaning protocol meant for the removal of elements in an equipment surface, such as organic fouling and scaling, using various solution types, such as acid and sanitizer, as cleaning agents. These processes illustrate CIP as an intensive industrial method for rinsing off varied effluents for sustainable wastewater treatment [20]. Proper and successful CIP practices ensure efficient operations and maintenance. In preserving the functional ability of the RO membrane system, CIP procedures are employed to extend the membrane's longevity by optimizing the performance of the system. Table 1 shows the processes and functions of a typical RO plant CIP protocol.

Table 1. A typical RO plant CIP process [21].

Process	Function

Pre-rinse	Displacing feedwater and confirming the CIP flow path
Low pH cleaning	Removing organic and biological materials from the membrane system
High pH cleaning	Removing foulants from the membrane system
Final rinse	Removing all cleaning chemicals
Quality rinse	Confirming the product quality is within suitable operating conditions

The efficiency of RO membrane maintenance practices is well explained on the basis of typical CIP protocols. A comparison made between CIP efficacy in lab-scale and full-scale RO investigated the suitability of laboratory and industrial membrane system pretreatment [22]. A significant difference between full-scale (9–20%) and lab-scale (~50%) was apparent. The disparity is explained by reviewing the results from the membrane fouling simulator in the lab-scale biofilms, which has a richness in polysaccharide ratio of 0.5, compared to the lab-scale membrane fouling simulator, which has full-scale modules containing polysaccharide ratio of 2.2. It is concluded that the development of CIP protocols should use synthetic feed water and fouling layers fabricated within a short period [22]. The relevance of CIP procedures in RO membrane systems cannot be overemphasized since they are crucial in ensuring ideal operational conditions. Moreover, a study [23] was performed at the Mahou-San Miguel brewing plant situated in Alovera, Spain to investigate the efficacy of CIP procedures to assist in restoring the permeability of the RO membrane system. The CIP protocol consisted of high-pressure backwash and soaking of sodium hypochlorite and hydrochloric acid dosing at 13% and 33%, respectively. The microfiltration membrane integrated sodium hypochlorite up to 3000 ppm and hydrochloric acid at 5%. Results revealed the effectiveness of using sodium hypochlorite as a cleaning agent since it restored permeability within a range of 50 to 120% while it eliminated organic matter and removed inorganic depositions, although the process incorporated a high chemical cost. The inference made in these accounts implies that various parameters other than materials and costs are considered when ideal operation conditions for a CIP should be achieved for efficiency and performance.

However, a study [25] that assessed the efficacy of CIP protocols on whey RO membranes provided varying findings. It consisted of experiments conducted using four replicates. Results revealed that the tested CIP protocol showed limited effectiveness in cleaning membrane biofilms in the whey RO membranes. Apparently, the conditions for cleaning RO membranes necessitate combining effective CIP procedures and the use of proper materials. The claim is affirmed by a review [26] that summarizes CIP practices in mitigating organic fouling when using ceramic membranes in processing liquids of organic origin. Therefore, the paper recommended sodium hydroxide, strong oxidants, or acids as efficient options in cleaning irreversible fouling treatment. The RO desalination pre-treatment should be optimized in such a manner that it does not affect the filtration performance. The assertion is associated with an explanation made in the study [27], which identifies that membrane cleaning procedure comprises the optimization of key operational parameters, the cost-effectiveness, and sustainability of the filtration operations to remove reversible fouling through chemical cleaning so as not to affect filtration. Thus, the underlying and most practical conditions for the cleaning efficiency of CIP have been explained. In their study, [28] clarified that evidence was required from a practical standpoint and a scientific view to expound on the underlying regulating mechanism for long-term CIP fouling control strategy in RO membranes. Thus, for improved RO operation sustainability to mitigate fouling, the selection of CIP procedures should manifest feasibility and sustainability. Figure. 3 illustrates the phase structure of a typical CIP application.

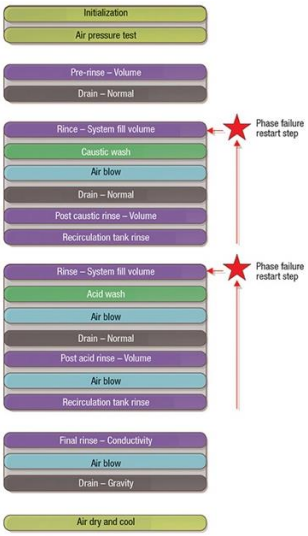

Figure 3. The phase structure of a typical CIP application [24].

2.3 Remaining Useful Life Predictive Modelling

Existing studies have explored varied opportunities and challenges of RUL predictive models in promoting reliability and accuracy utilizing collected data sets. Li, Wang, Wang, Xiao, and Huang, presented a deep learning-based RUL predictive modelling on RO membrane emphasizing weigh sequence data and proposed a method to improve accuracy and efficiency in the practical use of the distributed mechanism [28]. The context of the experiment encompassed the extraction of time series based on a verified commercial modular aero-propulsion system simulation (C-MAPSS) data set. The results show that the proposed method consisting of the weights of industrial sensors and time steps depicted high accuracy and sustained efficiency in practical applications. The development of an advanced analytical procedure using RUL boosts optimality when it comes to maintenance practices. Thus, researchers [29] developed a novel analytical procedure that estimated the RUL of complex industrial facilities based on the degradation data collected over time. They proposed to build an extended prognostic model to predict RUL in terms of maintenance aspects of incompletely repaired units. With the artificial neural network method, the RUL predictive model process was ascertained to yield low-cost prognostics, hence making the procedure effective in high-risk facilities since it assists in establishing optimality and satisfying necessary preventative maintenance practices. The advantage of proposing a novel modelling method is its feasibility in achieving valuable risk analysis and decision-making [30]. Prediction results aid in identifying and proposing a RUL model for forecasting the lifecycle of a system.

The RUL predictive modelling methods have challenges when adopting model-based data. The Wiener process-based method was offered to address challenges attributed to the random factors within RUL prediction [30]. This development is motivated by the idea to describe the limited performance of a degradation model since the Weiner process integrates a set of superior calculation analysis features and parameters to describe a random process. [30] employed the Wiener process to predict the RUL of an axial piston pump. The experimental results revealed that the method is crucial in indicating appropriate parameters for demonstrating the status of the axial piston pump in terms of its internal wear condition. Accordingly, increasing the accuracy of the RUL predictive model improves the system's reliability [31]. A study by Cheng and

colleagues [32], which developed a module to predict the RUL model (dual-channel long short-term memory LSTM neural network model) to improve prediction accuracy, concluded that the experimental verification on the commercial modular aerospace propulsion system simulation (C-MAPSS) dataset evidenced the stability and efficiency of an advanced predictive model to leverage RUL prediction complexity. Overcoming these challenges is a research area that attracts interest since there is a necessity to build a framework that will improve the RUL predictive process. A qualitative review [33] explored these limitations and proposed a compact framework as a solution to the complex RUL prediction process when the accuracy concern of the operational datasets is addressed. Eventually, building an integrated framework is essential when technological components are involved in managing huge datasets and used to trigger the system through the RUL predictive model for maintenance [33]. The evidence provides a deep insight into measures fundamental to assist in improving the RUL predictive model within the industrial context.

Reverse Osmosis (RO) desalination plants pose significant challenges due to their highly nonlinear multi-input-multioutput nature, which is compounded by uncertainties, constraints, and intricate physical phenomena like membrane fouling. Addressing these complexities demands effective control strategies, among which nonlinear model predictive control (NMPC) stands out [34]. NMPC, however, heavily relies on the accuracy of the internal model for prediction to ensure the RO desalination plant's operational feasibility. Recurrent Neural Networks (RNNs), particularly Long-Short-Term Memory (LSTM) networks, excel in capturing complex nonlinear dynamics and offering long-range predictions, even amidst disturbances. Thus, this study proposes an NMPC approach for an RO desalination plant employing an LSTM as the predictive model [34]. The controller is designed to regulate a specified permeate flow rate and maintain permeate concentration below a defined threshold by adjusting the feed pressure. Experimental results in the study demonstrate the efficacy of the proposed approach in achieving desired system performance [34].

Chapter 3. Research Methodology

This chapter presents the approach that was applied to develop a predictive model for estimating the remaining useful life (RUL) of SEWA's RO membrane system. A comprehensive methodology is required to achieve this objective. The intended outcome is to decrease pressure changes and the frequency of CIP by accurately predicting membrane longevity based on the parameters affecting its lifetime. The framework of this study is illustrated in Figure. 4, this methodology section outlines the procedures for collecting operational data from the RO units, including pressure changes and relevant membrane performance metrics. Additionally, it explains the approach used to gather laboratory results on feedwater parameters, such as dissolved solids. Data pre-processing techniques, including data cleaning and AI-based model development, are detailed in this section. Furthermore, the chapter integrates results analysis, which will encompass three phases: the interpretation of the predictive model's output, the analysis of CIP frequency, and the assessment of the predictive model's effectiveness in predicting membrane lifespan.

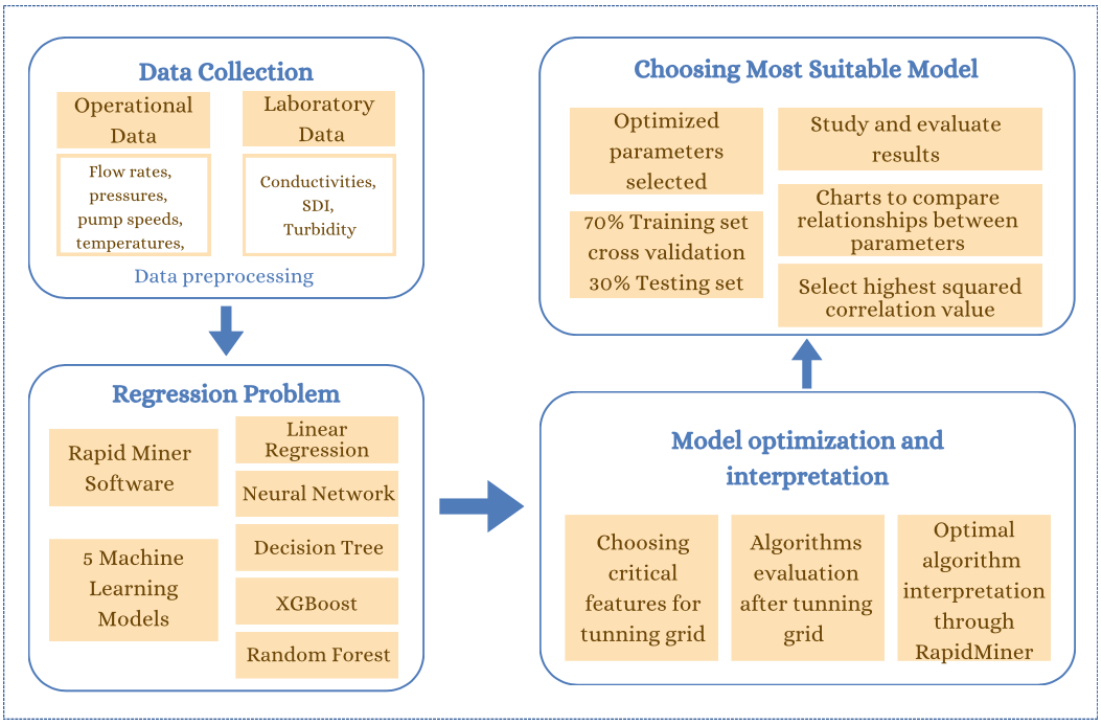

Figure 4: Research Framework and Methodology

3.1 Methodology

1. Data collection:

The proposed AI prediction model was developed based on data obtained from SEWA since the power station has an operational data unit. The reliability of this approach to data collection cannot be overstressed since AI techniques facilitate the processing of large datasets in the industrial context to develop operational and effective smart decisions on applications for risk factors analysis and maintenance [35]. Furthermore, the possibility of obtaining the lab results for the water parameters and all necessary information about the quality and conditions of the RO membrane system is guaranteed by this approach. The desalination system is an engineering process that requires the adoption of data-driven algorithms obtained from open sources and laboratory results to build an AI-based model [36]. Thus, the researcher will gather historical operational data from the desalination facilities of the RO unit. The approach is less costly since SEWA has an operational database that will aid in locating relevant data for the study, which will include the parameters of the RO membrane system, CIP records, laboratory results, and membrane analysis reports.

The RO system data collected from SEWA was structured with a total of 2999 instances and 34 attributes recorded covering the time period between January 1st, 2020 and August 31st, 2024. The raw attributes are presented in Table 2.

Table 2. Data Collected and its Description

Attribute	**Stage**	**Data Description**
Total Feed	RO inlet	The flow of inlet water to the RO system (m3/hr)
HP Pump	Pre-RO membranes	The flow of water in the high-pressure pump (m3/hr)
PX LP Inlet	Pre-RO membranes	The flow of inlet water in the pressure exchange low-pressure pump (m3/hr)
PX LP Outlet	Pre-RO membranes	The flow of outlet water in the pressure exchange low-pressure pump (m3/hr)
Permeate Avg	RO inlet	The average flow of treated permeate water (m3/hr)
Permeate Int	Post-RO membranes	The interval flow of treated permeate water (m3/hr)
Permeate Condty	Post-RO membranes	The conductivity of permeate water (µS)
Feed Pressure	RO inlet	Initial pressure of feed in the membrane (Bar)
Pump Speed HP	Pre-RO membranes	Speed of the high-pressure pump (%)

Pump Speed PX	Pre-RO membranes	Speed of the pressure exchange pump (%)
DAF Flow	Pretreatment	The flow of inlet water to the Dissolved air flotation tank (m^3/hr)
DP DMF Stage 1	Pretreatment	Change of pressure in the Dual media filtration in stage 1 tank (bar)
DP DMF Stage 2	Pretreatment	Change of pressure in the Dual media filtration in stage 2 tank (bar)
DP Cartridge Filter	Pretreatment	Change of pressure in the cartridge filter (bar)
Feed Water Condty	RO inlet	The conductivity of the RO feed water (µS)
Feed Water SDI	RO inlet	The SDI of the RO feed water
Feed Water Temp	RO inlet	The temperature of the RO feed water (°C)
SW in	RO inlet	The turbidity of seawater inlet (NTU)
DMF 1 out	Pretreatment	The turbidity of outlet water from the dual media filtration 1st stage
DMF 2 out	Pretreatment	The turbidity of outlet water from the dual media filtration 2st stage

From the raw features presented above, additional extracted features were generated to enhance the dataset with more attributes. These new features were constructed to enrich the operational data, providing a more comprehensive basis for predictive modeling. This expanded feature set was intended to capture additional patterns and trends within the data, ultimately contributing to a more robust and accurate predictive framework. The extracted features are presented in Table 3. The raw attributes from different data sets along with the extracted features has been combined into one comprehensive set, partially shown in Table 4, for the modelling process.

Table 3 Extracted Attributes and the Description

Extracted Attribute	**Data Description**
RUL	The remaining useful lifetime is measured by the amount of water (m^3) that can be produced till the next CIP
Age m^3	The age is measured by the amount of water (m^3) produced at the specific time
Min Permeate Condty	The minimum conductivity of permeate water since the last CIP (µS)
Max Permeate Condty	The maximum conductivity of permeate water since the last CIP (µS)

Mean Permeate Condty	The average conductivity of permeate water since the last CIP (µS)
Min Feed Water Condty	The minimum conductivity of feed water since the last CIP (µS)
Max Feed Water Condty	The maximum conductivity of feed water since the last CIP (µS)
Mean Feed Water Condty	The average conductivity of feed water since the last CIP (µS)
Min Feed Water SDI	The minimum SDI value of the feed water since the last CIP
Max Feed Water SDI	The maximum SDI value of the feed water since the last CIP
Mean Feed Water SDI	The average SDI value of the feed water since the last CIP
Min Feed Water Temp	The minimum temperature of feed water since the last CIP (°C)
Max Feed Water Temp	The maximum temperature of feed water since the last CIP (°C)
Mean Feed Water Temp	The average temperature of feed water since the last CIP (°C)

Table 4. Partial Set of the Data Collected

Total Feed	HP pump	PX LP inlet	PX LP outlet	Permeate Avg	Permeate Int	Permeate Condty	Feed Pressure	Pump Speed HP
1122	490	633	645	465	462.2916667	309	65.8	87.9
1126	492	627	638	465	466.1363636	303	65.9	87.8
1127	493	631	647	465	467.1627907	361	65.2	87.5
1118	490	623	646	465	462.25	342	65.3	87.5
1127	491	635	649	465	462.25	332	65.6	87.8
1132	490	630	645	465	462.25	324	65.9	87.7
1114	490	626	640	465	462.2916667	323	66.7	88.2
1120	490	630	643	465	462.0833333	317	66.4	88.2
1124	490	633	642	465	462	310	66.2	88.1
1124	489	631	643	465	465.6888889	310	66.4	88.2
1120	490	623	641	465	461.75	335	65.7	87.8
1118	489	630	643	465	462.125	297	66.2	88
1115	489	630	640	465	462.125	291	66.3	88.2
1119	489	626	645	465	462.0416667	290	66.5	88.4
1121	490	627	639	465	462.0833333	287	66.7	88.4
1120	491	630	642	465	462.0416667	284	66.7	88.3
1119	488	629	642	465	462	283	66.6	88.3
1115	489	628	641	465	462.0833333	281	66.8	88.3
1120	488	630	645	465	462.0416667	281	66.8	88.5
1110	490	625	638	465	462.0416667	281	67	88.6

2. Data pre-processing:

The research undertook a pre-processing step in developing an AI-based predictive model. In this case, various techniques and steps are integrated to ascertain operational data are used, such as data cleaning, reduction, scaling, transformation, and partitioning [37]. Data cleaning includes identifying and handling missing datasets using imputation techniques, for example, regression-

based analysis and mean, to enhance data quality. Similarly, using statistical methods removes outliers and aids in transforming them, which could involve logarithmic transformation. Data scaling incorporates classifying into similar ranges to ease data distribution and data structuring. The step enables one to encode data, after which feature engineering is done to represent patterns based on the RO parameters. Thus, data transformation ensures data compatibility through encoding. Finally, data partitioning entails splitting the datasets into subsets to train sets for model evaluation. Figure. 5 illustrates the data pre-processing steps conducted for developing operational data.

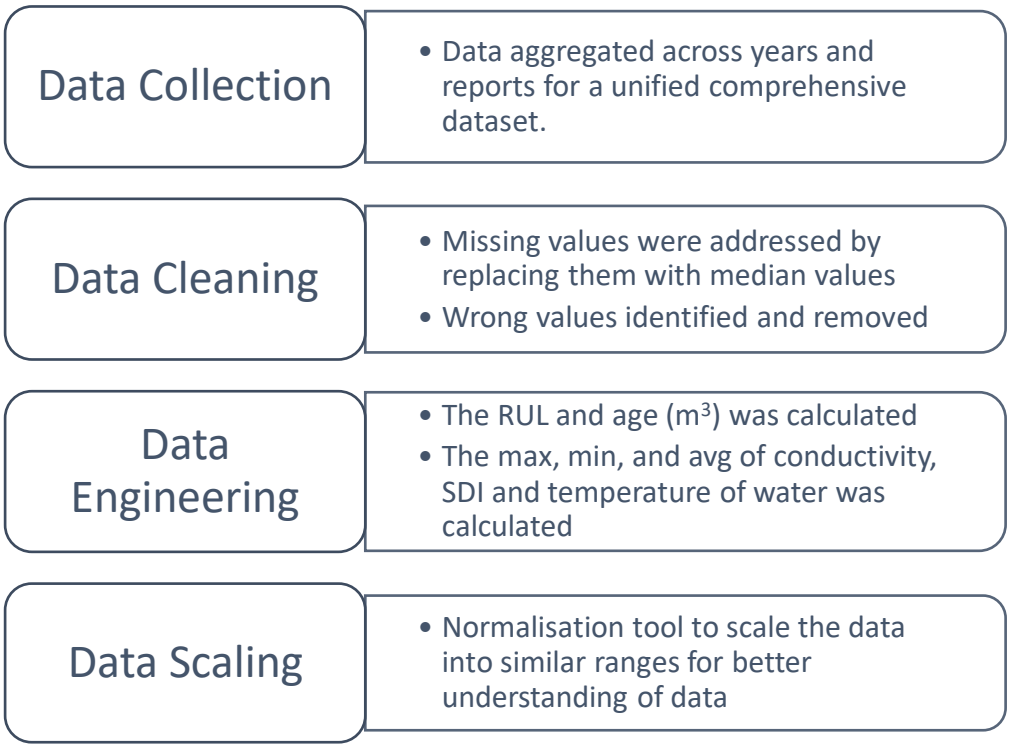

Figure 5 Data pre-processing steps conducted

3. Model development:

The study aims to explore and evaluate various artificial intelligence (AI) models to construct a robust predictive framework. Recent research [38] suggests that machine learning (ML) techniques, including Decision Trees (DTs), Random Forests (RF), Artificial Neural Networks (ANNs), XGBoost, and Support Vector Machines (SVM), exhibit promising potential in optimizing seawater desalination processes. These models are adept at leveraging real-time data to enhance operational efficiency in water treatment procedures. Furthermore, ANNs have showcased their utility in both

laboratory-scale investigations and commercial desalination plants for process optimization [39]. In line with the study's objectives, the suitability of various ML algorithms was assessed using numerical data extracted from the SEWA operational database and laboratory experiments. Given that the dataset comprised numerical data suited to a regression problem, not all machine learning algorithms in Altair Studio were suitable. Many algorithms are designed for classification tasks rather than regression. Consequently, algorithms like Decision Tree, Linear Regression, Neural Network, XGBoost, and Random Forest were identified as the most appropriate due to their effectiveness in handling regression tasks. To optimize the performance of each algorithm, a range of parameters was systematically evaluated. The performance of these models was determined through rigorous training and validation processes, with the algorithm exhibiting the highest correlation percentage identified as the best predictive model for estimating RUL of RO desalination system. Furthermore, maintenance strategies informed by the RUL predictions was implemented to enhance the performance and longevity of the RO membrane system.

3.2 Result Analysis

1) Predictive model output interpretation: Data-driven decisions optimize RO membrane maintenance since the CIP procedures are scheduled to extend the system's lifespan [12]. It is expected that the continuous optimization of the operational parameters will minimize the accumulation of particles to limit clogging. Therefore, performing feature analysis is an opportunity to identify the significant results of the RUL predictions. Additionally, sensitivity analysis to quantify the importance of the features will be done together with activation analysis to understand the reaction of the AI models to the inputted values. This procedure will be important to assist in comprehending the RUL in making its predictions utilizing AI modelling.

2) RUL Analysis for CIP Frequency: The recorded lab results will aid in evaluating the Remaining Useful Life (RUL) of the RO membrane system. Determining the criteria for membrane degradation helps to establish replacement rates, as the CIP frequency directly impacts the costs associated with downtime [40]. This process will involve identifying parameters that signal a decline in membrane performance, prompting CIP interventions. By examining historical data and assessing lab results, the relationship between CIP frequency and membrane RUL will be analyzed.

3) Predictive model assessment: Ensuring the effectiveness and reliability of the developed predictive model was paramount. This was achieved through a comprehensive assessment framework encompassing data splitting, model training, and metric evaluation. The dataset was divided into training and testing sets to assess model performance, and algorithm selection was conducted to optimize parameters for predictive accuracy. Standard regression metrics, including squared correlation (R^2), root mean squared error (RMSE), and mean absolute error (MAE), were employed for interpretation. The evaluation focused on the stability and robustness of the model, aiming to elucidate its decision-making process.

Chapter 4. Results and Discussion

4.1 R-Software

In the field of predictive modelling, R Software is a powerful and flexible tool for constructing advanced models that reveal valuable insights and forecast trends. In this study, R Software was used to develop a predictive model to estimate the remaining useful lifetime. The problem was framed as a regression problem, a type of predictive modelling where the objective is to predict continuous outcome variables (dependent variables) based on one or more predictor variables (independent variables). This approach involved learning the relationship between the inputs and outputs, enabling the model to make accurate predictions for new data.

As a start, the pre-processing of the data was conducted using R Software, where missing values were replaced with median values. Figure 6 illustrates the modelling and validation process performed in the software for the predictive model.

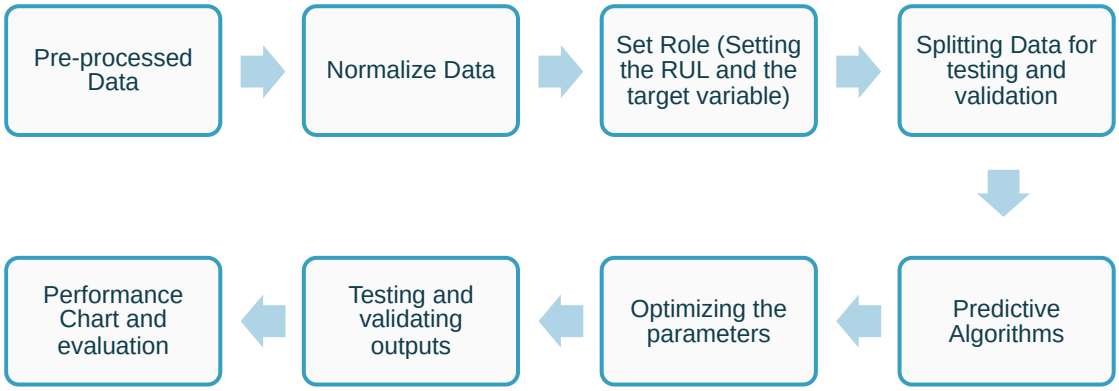

Figure 6 Modelling and Validation Process

The process consists of three main sections: data preprocessing, splitting the data for the predictive algorithms, and validating and testing the performance of the model. The data was divided using a 70:30 ratio for training and testing purposes following recommendations found in the literature. Additionally, an optimization operator was implemented to fine-tune the parameters of the algorithms. The optimization parameters utilized in the modelling are as follows in Table 5:

Table 5 Modelling Parameters

Algorithm	**Tunning Parameters**	**Optimal Parameter Value**
Linear Regression	No Tunning	-
Decision Tree (CART)	1. Cost Complexity [1e-10 to 0.1] 2. Tree Depth [1 to 15]	1. Cost Complexity = 0.00001 2. Tree Depth = 15
XGBoost	1. Mtry (number of random variable selection) [1 to 20] 2. No. of trees [1 to 2000]	1. Mtry (number of random variable selection) = 20 2. No. of trees= 1333
Random Forest	1. Mtry [1 to 20] 2. No. of trees [1 to 2000]	1. Mtry = 11 2. No. of trees= 445

4.1.1. Tunning parameters results

The following charts in Figures 7, 8 and 9, represent the tunning parameters for each of the predictive algorithms, alongside their corresponding performance metrics. The R-squared (R^2) coefficient is shown, which measures how well the model's predictions align with the actual data; higher R^2 values indicate better model fit. Additionally, the Root Mean Squared Error (RMSE) is presented, which measures the square root of the average squared differences between the predicted and actual values, with lower RMSE values reflecting better model accuracy. The Mean Absolute Percentage Error (MAPE) is also included, indicating the average absolute percentage difference between the predicted and actual values. Finally, the Mean Absolute Error (MAE) is displayed, measuring the average of the absolute differences between the predicted and actual values. For error-based metrics such as RMSE, MAPE, and MAE, lower values signify better model performance. By comparing the parameters and metrics displayed in the charts, the optimal parameters for each algorithm can be identified, ensuring the best performance of the predictive model.

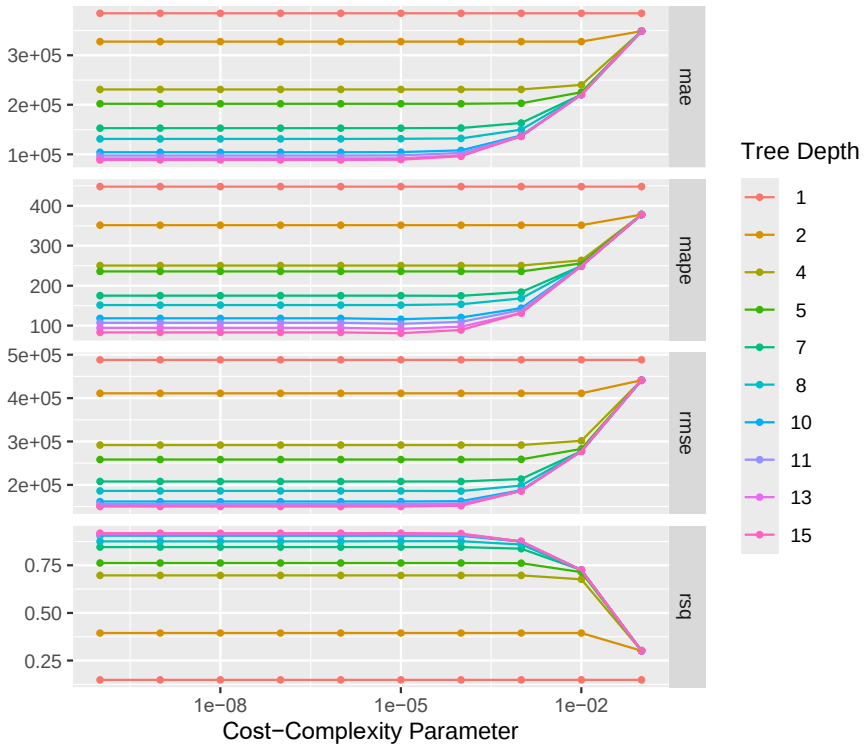

Figure 7 Tunning parameters results for Decision Tree (CART)

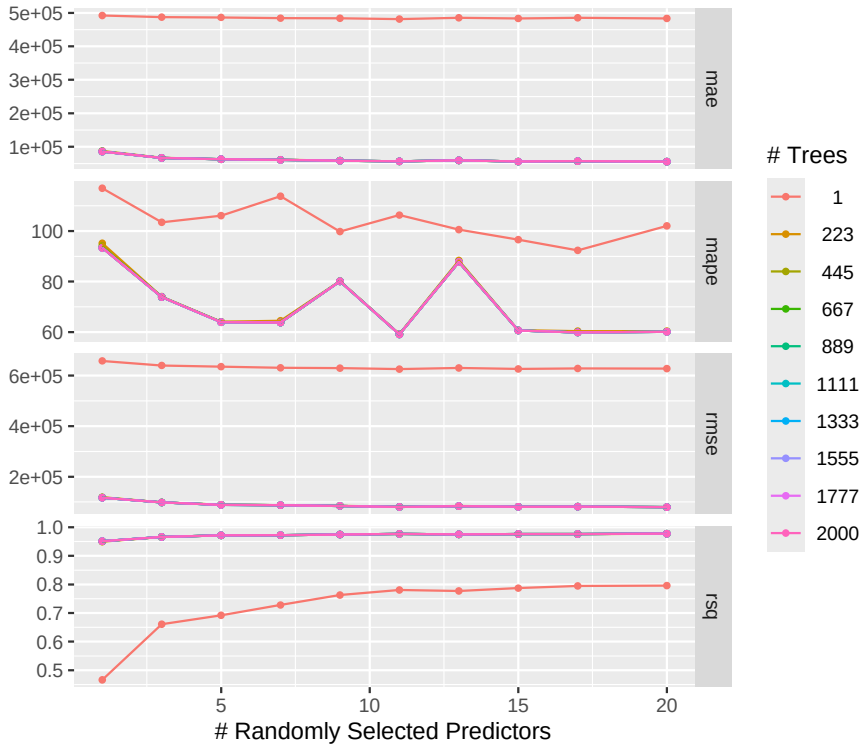

Figure 8 Tunning Parameters Results for XGBoost

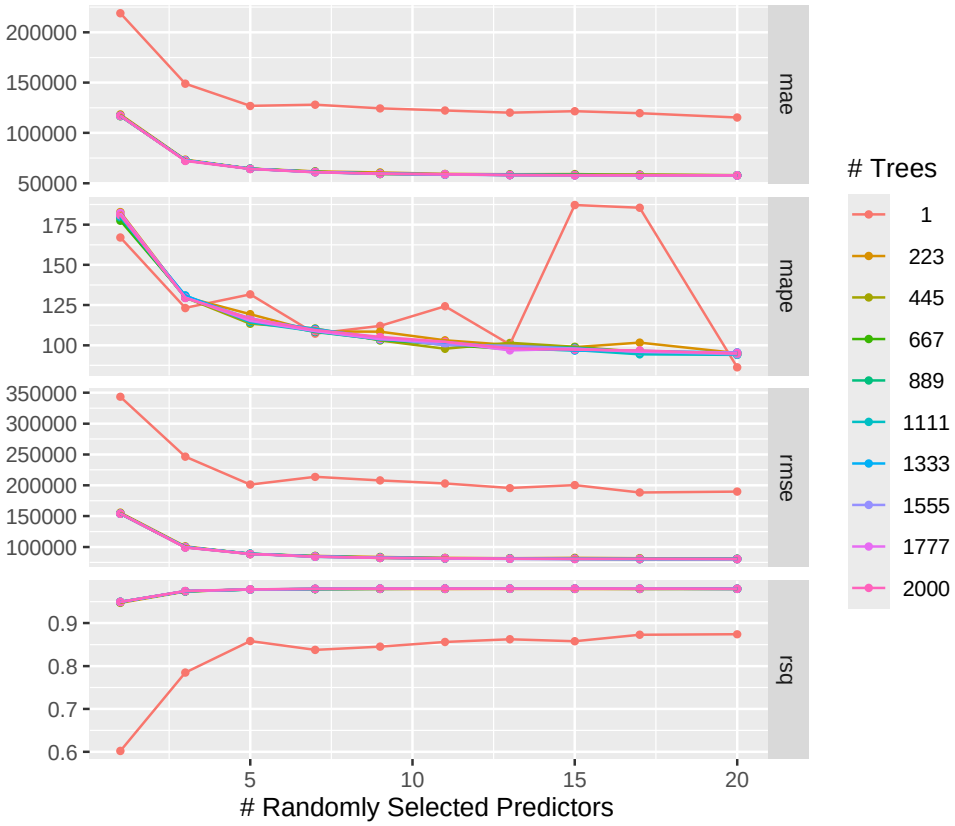

Figure 9 Tunning Parameters Results for Random Forest

The scatter chart clearly demonstrates that the squared correlation increases as the minimum tolerance parameter decreases, a trend that is consistent across all steps tested for this model.

The primary objective in developing these predictive models is to maximize the squared correlation and to minimize the root mean squared error. Maximizing the R^2 is important because it indicates a stronger linear relationship between predicted and actual values. Minimizing the RMSE reduces prediction errors, indicating higher accuracy by showing that the predicted values closely match the actual values. Through the evaluation of various parameters and subsequent optimization, Table 6 presents the enhanced performance metrics for each algorithm.

Table 6 Performance of the predictive algorithms

	Performance

Predictive Algorithm	R^2	RMSE	MAE
Linear Regression	0.655	0.571	0.431
Decision Tree (CART)	0.936	0.246	0.152
XGBoost	0.977	0.147	0.0993
Random Forest	**0.984**	**0.136**	**0.0997**

As highlighted, the random forest model achieved the best performance, with an R^2 of 0.984. This indicates that the model accurately predicts the RUL values of the membranes. Moreover, The RMSE value for the random forest model was also one of the lowest, at 0.136, demonstrating its precision in forecasting. The lowest RMSE among the algorithms tested was from XGBoost, with a value of 0.147, which is quite similar. The results of the Random Forest algorithm demonstrate the exceptional performance of the predictive model, highlighted by its high R-squared coefficient and impressive accuracy percentage. These findings underscore the model's reliability and effectiveness, making it a robust tool for forecasting the remaining useful life of reverse osmosis membranes.

4.1.2. Model performance and validation

The following chart illustrates the comparison between the actual RUL values and the predicted RUL values generated by the Random Forest model. The points in the chart in Figure 10, closely align with the correlation line, indicating a high degree of correlation between the actual and predicted values. The minimal scattering of points away from the line further demonstrates the exceptional accuracy and reliability of the Random Forest model in predicting the RUL. This visual representation reaffirms the model's outstanding performance and its suitability for use in predictive maintenance applications.

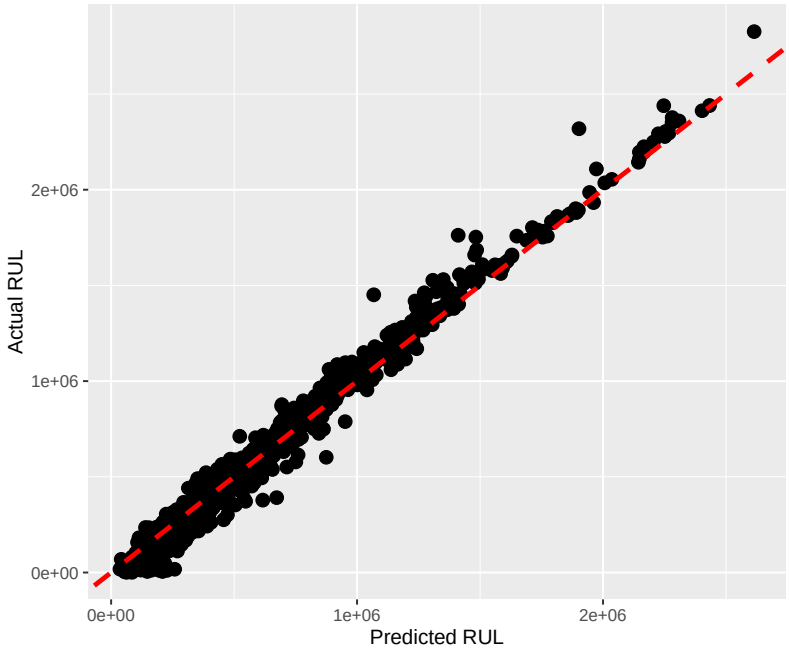

Figure 10 Actual Vs. Predicted RUL Values Graph

The following figures display two error graphs: the probability density function (PDF) in Figure 11 and the cumulative probability density (CPD) function in Figure 12. These graphs help evaluate the performance of the models based on their error distributions. It is important to note that the errors shown are normalized rather than actual values, ensuring that all data is scaled within a similar range for comparison.

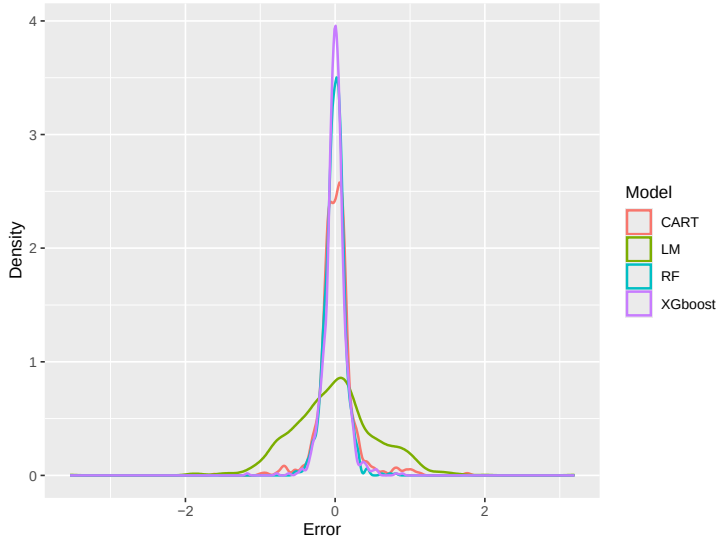

Figure 11 Probability Density Function Graph

In the PDF graph, a narrower variance or range of the line indicates a smaller error distribution, signifying better model performance. From the chart, it is evident that

CART, Random Forest, and XGBoost exhibit similar performance with narrow distributions.

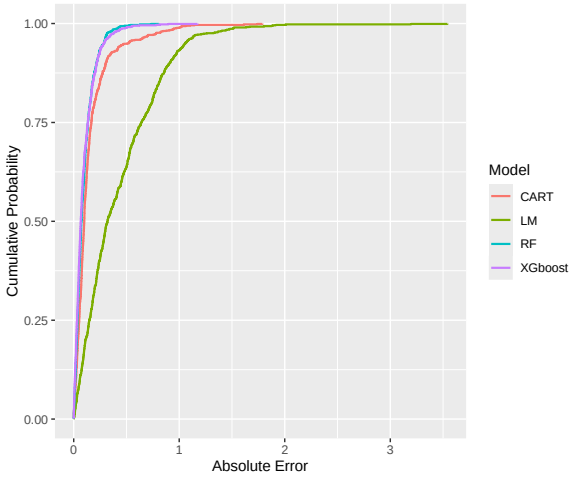

Figure 12 Cumulative Probability Density Graph

In the CPD function graph, the closer a model's line is to the upper-left corner, the better its performance, as this reflects lower variance and a faster cumulative reach to 100%. From this chart, the Random Forest model stands out as the best-performing algorithm among all, demonstrating its superior accuracy and reliability.

4.1.3. Variable importance

After evaluating the performance of various models and selecting the Random Forest algorithm as the best predictive model, it became evident that identifying the variables with the most significant impact on the remaining useful life of reverse osmosis membranes was crucial. Understanding which features most strongly influence membrane lifespan provides valuable insights into the operational conditions of the plant, allowing for informed decisions to optimize performance and extend membrane longevity.

The first bar chart presented in Figure 13 illustrates the variable importance as determined by the Random Forest model. This chart highlights the general significance of each feature, offering an overview of the factors that have the greatest impact on RUL predictions.

In addition to the Random Forest variable importance chart, two SHAP graphs are included to provide further insights. The global SHAP importance graph in Figure 14, reveals the significance of features across the entire dataset, identifying which variables

consistently contribute to the model's decisions. Meanwhile, the local SHAP importance graph in Figure 15, delves into individual predictions, explaining why the model made a specific decision for a particular instance. This graph is represented in dot form, where the colour gradient indicates the level of impact, with highly influential features shown in distinct colours. Together, these visualizations offer a comprehensive understanding of the factors affecting RUL and enable targeted improvements in plant operations.

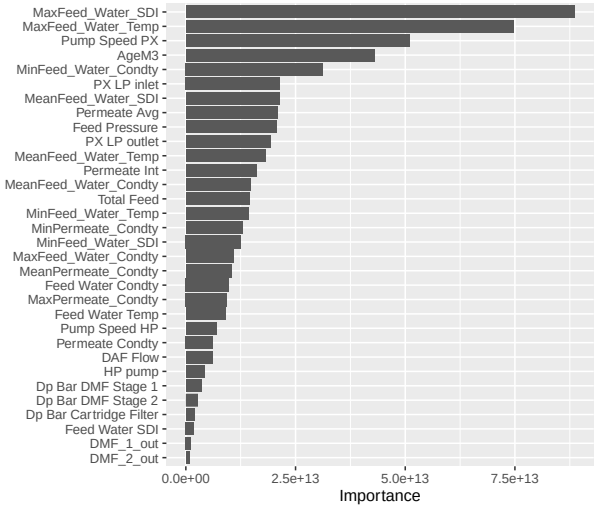

Figure 13 RF Variable Importance Graph

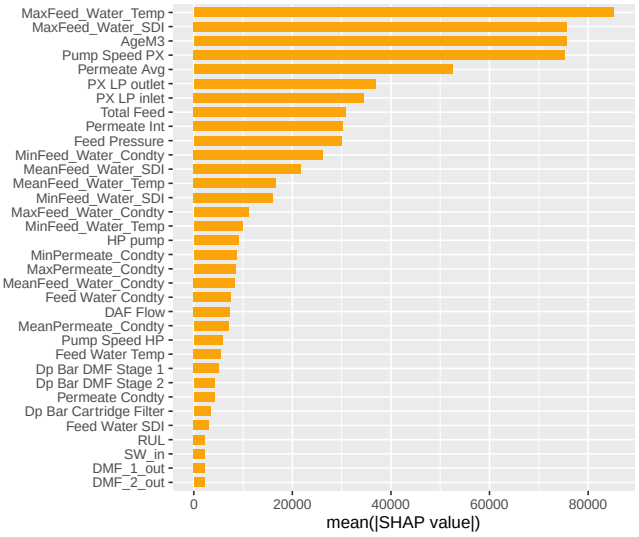

Figure 14 SHAP Global Importance

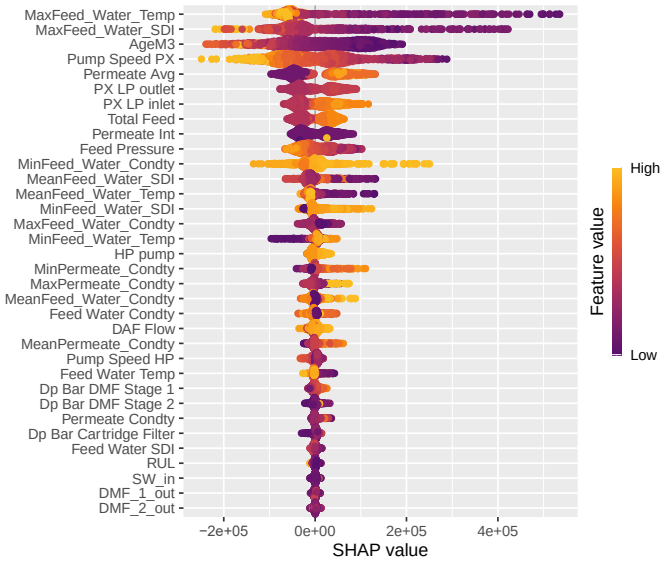

Figure 15 SHAP Local Importance

The analysis of variable importance across all charts reveals that the top four features significantly influencing the RUL of the RO membranes are the Silt Density Index (SDI), water temperature, pump speed, and the membrane age (m^3). These variables are inherently linked to the performance and degradation of the membranes, making their high influence on the RUL logical and expected.

Starting with the SDI, this metric assesses the fouling potential of the water by measuring the presence of suspended solids, particles, and other fouling agents that can clog the membranes. A high SDI value typically indicates a greater risk of fouling, thereby reducing the membrane's lifespan.

Next is the water temperature, which directly impacts the solubility of fouling agents and the viscosity of water. Temperature fluctuations can also affect membrane degradation, with membrane design limits generally between 5°C and 45°C. Maintaining optimal temperatures is critical, as higher temperatures can increase scaling due to salt precipitation or reduce the solubility of salts such as calcium carbonate and sulfate, thereby exacerbating fouling.

The third key variable is the pump speed. While higher pump speeds can improve feed water flow and enhance turbulence across the membrane surface—helping to reduce biofouling and scaling—excessively high speeds can cause membrane compaction, which diminishes its lifespan.

Lastly, the age of the membrane, as expected, strongly influences RUL. Older membranes naturally exhibit reduced performance and a shorter remaining lifespan due to prolonged exposure to operational stresses.

Overall, this analysis underscores the significant role operational data plays in determining membrane performance and lifespan. By monitoring and optimizing these critical variables, RO plants can operate under optimal conditions, ultimately extending membrane longevity and enhancing overall system efficiency.

Chapter 5. Summary and Conclusions

The successful completion of the predictive modeling for the remaining useful life (RUL) of reverse osmosis (RO) membranes marks a significant advancement in the maintenance and management of RO systems. Through the examination of the literature and an extensive analysis of the dataset, five primary algorithms were tested: linear regression, decision tree, neural networks, XGBoost, and random forest. Among these, the random forest algorithm demonstrated the best performance, achieving an impressive accuracy of 98.4% for the tested values. This high level of accuracy confirms that the random forest model can be effectively employed to predict the RUL of RO membranes, ultimately benefiting water treatment plants by enhancing maintenance strategies. By accurately forecasting the lifespan of membranes, this predictive model can minimize unexpected failures and reduce the frequency of cleaning in place (CIP) procedures, thus optimizing operational efficiency.

The development of this AI-based predictive model is underpinned by a robust methodology that leverages both experimental and historical operational data. It addresses critical challenges in managing RO membrane performance, particularly in mitigating the impacts of pressure changes that could lead to fouling and damage. This research not only contributes to the field of predictive maintenance in desalination but also enhances data-driven decision-making processes. Ultimately, the findings of this thesis have the potential to advance knowledge regarding optimal operating conditions and parameters necessary for effective seawater treatment. By leveraging AI in predictive maintenance, we can improve the cost-effectiveness and efficiency of desalination processes, thus extending the lifespan of RO membranes and supporting sustainable seawater production practices.

5.1 Limitations and Constraints

The proposed research has potential significance based on its implications and contributions, while methodology and data interpretation limitations and constraints need adequate consideration. The accuracy of the remaining useful life (RUL) predictions is heavily dependent on the quality and availability of data from SEWA; any inconsistencies or gaps could compromise model performance. Furthermore, the complexity of the predictive models, particularly the random forest algorithm, poses challenges in balancing accuracy with interpretability, necessitating careful parameter

selection. However, the model's high accuracy of 98% demonstrates its practical value and potential for effective implementation. Achieving reliable results will necessitate the selection of an algorithm analysis that enables the researcher to identify and choose the most preferable input parameters that show the relationship between the input operational data and the target parameters [41]. Additionally, while external factors influencing membrane performance may remain beyond the model's control, ongoing monitoring and adaptation can help address these uncertainties. Successful collaboration with SEWA is crucial to access comprehensive operational data, enhancing the model's applicability and supporting effective maintenance strategies. Overall, addressing these constraints will not only ensure the validity and reliability of the research findings but also facilitate the development of a robust tool for optimizing RO membrane performance in real-world applications.

5.2 Conclusion and Future Work

In conclusion, this research has successfully developed a predictive model for estimating the remaining useful life of the RO membranes, achieving a notable accuracy of 98% with the random forest algorithm. This model provides a valuable tool for optimizing maintenance strategies, thereby enhancing the operational sustainability of desalination processes.

For future work, it is essential to test the model on a new dataset to validate its robustness and adaptability in different operational conditions. Additionally, implementing the model within SEWA's existing RO systems could provide real-time predictions and further refine maintenance practices. To build an optimization model for the CIP scheduling to achieve the ultimate goal of maximizing the RUL would also be a critical next step. Exploring the integration of the model with advanced monitoring technologies, such as IoT sensors, could enhance its predictive capabilities and facilitate proactive maintenance interventions. Furthermore, ongoing collaboration with SEWA will be crucial for continuously improving the model and ensuring it meets the practical needs of desalination operations. This research lays the foundation for further innovations in predictive maintenance, ultimately contributing to more efficient and sustainable water treatment solutions.

References

[1] S. Alaa Abu, N. Tasmin, and A. Amer, "Potable water in UAE: An overview of water characteristics and sources of contamination," *J Environ Toxicol Stud*, vol. 3, no. 2, pp. 1–4. Mar. 2019, doi: https://doi.org/10.16966/2576-6430.120.

[2] A. S. K. Darwish, "Wind energy utilisation for water desalination, street and buildings lighting − A case study for the Emirate of Ajman − UAE," *Renewable Energy Environ Sustainability*, vol. 6, p. 10, 2021, doi: https://doi.org/10.1051/rees/2021012.

[3] R. AL-Dabbagh, A. S. Darwish, and Naser W. Alnaser, "Management practices of conventional and non-conventional water resources: study case in Emirate of Sharjah, UAE," *Arab Gulf J of Scientific Research*, vol. 38, no. 3, pp. 149–171. 2020. Accessed: Dec. 6, 2023. [Online]. Available: https://agjsr.agu.edu.bh/uploads/images/papers/pdfs/1c3c79a4d7ed07d307646e20180b89c7_61a4a8771ad71.pdf#:~:text=Water%20Management%20in%20The%20Emirate,and%20treated%20wastewater%2C%20Figure%206.

[4] A. Alsharhan, Z. Rizk, "Water resources and water demands in the UAE," In *Water Resources and Integrated Management of the United Arab Emirates*, pp. 757–791, 2020, doi: http://dx.doi.org/10.1007/978-3-030-31684-6_27

[5] UAE G. P., "Sewerage projects | The Official Portal of the UAE Government," *U.ae*, 2021. Accessed Dec. 05, 2023. [Online]. Available: https://u.ae/en/information-and-services/infrastructure/%20civic-facilities/sewerage-projects

[6] T. Shivakumar and V. Razaviarani, "An integrated approach to enhance the desalination process: coupling reverse osmosis process with microbial desalination cells in the UAE," *Water Supply*, vol. 21, no. 3, pp. 1127–1143, Dec. 2020, doi: https://doi.org/10.2166/ws.2020.375.

[7] L. V. Amma and F. Ashraf, "Brine management in reverse osmosis desalination: A UAE perspective," *2020 Advances in Science and Engineering Technology International Conferences (ASET)*, Feb. 2020, doi: https://doi.org/10.1109/aset48392.2020.9118335

[8] B. Zolghadr-Asli *et al.*, "A review of limitations and potentials of desalination as a sustainable source of water," *Environmental Sci and Pollution Research*, Nov. 2023, doi: https://doi.org/10.1007/s11356-023-30662-x.

[9] S. Bhattacharjee, G. Dersel, A. Shanableh, N. Darwish, and M. Al-Samarai, "Challenges & opportunities of wastewater reuse privatization: a case study from Sharjah, UAE," *IEEE Xplore*, Feb. 2020. Accessed: Dec. 6, 2023. [Online]. Available at: https://ieeexplore.ieee.org/document/9118342

[10] Rasha. Saeed, A. H. Konsowa, M. S. Shalaby, M. S. Mansour, and M. G. Eloffy, "Optimization of integrated forward – Reverse osmosis desalination processes for

brackish water," *Alexandria Engineering J*, vol. 63, pp. 89–102, Jan. 2023, doi: https://doi.org/10.1016/j.aej.2022.07.054.

[11] N. AlSawaftah, W. Abuwatfa, N. Darwish, and G. Husseini, "A comprehensive review on membrane fouling: Mathematical modelling, prediction, diagnosis, and mitigation," *Water*, vol. 13, no. 9, pp. 1–37, Jan. 2021, doi: https://doi.org/10.3390/w13091327.

[12] S. Eltanbouly, A. Erradi, A. Tantawy, A. B. Said, K. Shaban, and Hazim Qiblawey, "LIME: long-term forecasting model for desalination membrane fouling to estimate the remaining useful life of membrane," *Intern Confer on Industrial, Engineering and Other Applications of Applied Intelligent Syst*, pp. 3–14, Jan. 2023, doi: https://doi.org/10.1007/978-3-031-36822-6_1.

[13] Y. Ibrahim and N. Hilal, "Enhancing ultrafiltration membrane permeability and antifouling performance through surface patterning with features resembling feed spacers," *npj Clean Water*, vol. 6, no. 1, pp. 1–15, Sep. 2023, doi: https://doi.org/10.1038/s41545-023-00277-3.

[14] R. Cruz-Silva *et al.*, "Nanocomposite desalination membranes made of aromatic polyamide with cellulose nanofibers: Synthesis, performance, and water diffusion study," *Nanoscale*, vol. 12, no. 38, pp. 19628–19637, Oct. 2020, doi: https://doi.org/10.1039/d0nr02915g.

[15] T. Tavares, J. Tavares, F. León, Baltasar Peñate, and Alejandro Ramos Martín, "Assessment of processes to increase the useful life and the reuse of reverse osmosis elements in Cape Verde and Macaronesia," *Membranes*, vol. 12, no. 6, pp. 613–613, Jun. 2022, doi: https://doi.org/10.3390/membranes12060613.

[16] A. Zapata-Sierra, M. Cascajares, A. Alcayde, and F. Manzano-Agugliaro, "Worldwide research trends on desalination," *Desalination*, vol. 519, p. 115305, Dec. 2021, doi: https://doi.org/10.1016/j.desal.2021.115305.

[17] M. A. Ahmed, S. Amin, and A. A. Mohamed, "Fouling in reverse osmosis membranes: monitoring, characterization, mitigation strategies and future directions," *Heliyon*, p. e14908, Mar. 2023, doi: https://doi.org/10.1016/j.heliyon.2023.e14908.

[18] M. Qasim, M. Badrelzaman, N. N. Darwish, N. A. Darwish, and N. Hilal, "Reverse osmosis desalination: A state-of-the-art review," *Desalination*, vol. 459, pp. 59–104, Jun. 2019, doi: https://doi.org/10.1016/j.desal.2019.02.008.

[19] W. H. Abuwatfa, N. AlSawaftah, N. Darwish, W. G. Pitt, and G. A. Husseini, "A review on membrane fouling prediction using Artificial Neural Networks (ANNs)," *Membranes*, vol. 13, no. 7, Jul. 2023, doi: https://doi.org/10.3390/membranes13070685.

[20] Y. Su and C. Jacobsen, "Treatment of clean in place (CIP) wastewater using microalgae: Nutrient upcycling and value-added byproducts production," *Science of The Total Environment*, vol. 785, p. 147337, Sep. 2021, doi: https://doi.org/10.1016/j.scitotenv.2021.147337.

[21] J. Bailey, “Membrane CIP (Clean in Place): A Complete Guide,” *Avista Membrane Treatment Solutions*, Oct. 2022. Accessed: Dec. 6, 2023. [Online]. Available at: https://avistamembranesolutions.com/resources/membrane-cip-clean-in-place-a-complete-guide/

[22] M. Jafari *et al.*, “A comparison between chemical cleaning efficiency in lab-scale and full-scale reverse osmosis membranes: Role of extracellular polymeric substances (EPS),” *J Membrane Science*, vol. 609, pp. 118189–118189, Aug. 2020, doi: https://doi.org/10.1016/j.memsci.2020.118189.

[23] M. S. Toran *et al.*, “Membrane-based processes to obtain high-quality water from brewery wastewater, “*Front Chem Eng* vol. 3, Sep. 2021, doi: https://doi.org/10.3389/fceng.2021.734233.

[24] T. Previs, L. R. Seiberling, “Methods to achieve sustainable clean-in-place,” *Haskell*, Apr. 05, 2018. Accessed: Dec. 6, 2023. https://www.haskell.com/insights/methods-to-achieve-sustainable-clean-in-place/.

[25] D. Singh and S. Anand, “Efficacy of a typical clean-in-place protocol against in vitro membrane biofilms,” *J Dairy Science*, Oct. 2022, doi: https://doi.org/10.3168/jds.2022-21712.

[26] K. Gruskevica and L. Mezule, “Cleaning methods for ceramic ultrafiltration membranes affected by organic fouling,” *Membranes*, vol. 11, no. 2, Feb. 2021, doi: https://doi.org/10.3390/membranes11020131.

[27] S. Brover, Y. Lester, A. Brenner, and E. Sahar-Hadar, “Optimization of ultrafiltration as pre-treatment for seawater RO desalination,” *Desalination*, vol. 524, Feb. 2022, doi: https://doi.org/10.1016/j.desal.2021.115478.

[28] Y. Li, H. Wang, S. Wang, K. Xiao, and X. Huang, “Enzymatic cleaning mitigates polysaccharide-induced refouling of RO membrane: Evidence from foulant layer structure and microbial dynamics,” *Environmental Science & Technology*, vol. 55, no. 8, pp. 5453–5462, Jan. 2021, doi: https://doi.org/10.1021/acs.est.0c04735.

[29] Y. Song, S. Gao, Y. Li, L. Jia, Q. Li, and F. Pang, “Distributed attention-based temporal convolutional network for remaining useful life prediction,” *IEEE Internet of Things J*, vol. 8, no. 12, pp. 9594–9602, Jun. 2021, doi: https://doi.org/10.1109/jiot.2020.3004452.

[30] X. Wang, S. Lin, S. Wang, Z. He, and C. Zhang, “Remaining useful life prediction based on the Wiener process for an aviation axial piston pump,” *Chinese J Aeronautics*, vol. 29, no. 3, pp. 779–788, Jun. 2016, doi: https://doi.org/10.1016/j.cja.2015.12.020.

[31] M. Yan, X. Wang, B. Wang, M. Chang, and I. Muhammad, “Bearing remaining useful life prediction using support vector machine and hybrid degradation tracking model,” vol. 98, pp. 471–482, Mar. 2020, doi: https://doi.org/10.1016/j.isatra.2019.08.058.

[32] P. Cheng, J. Wu, Q. Wang, W. Gui, and Z. Tang, “Remaining useful life prediction using dual-channel LSTM with time feature and its difference,” *Entropy*, vol. 24, no. 12, pp. 1818–1818, Dec. 2022, doi: https://doi.org/10.3390/e24121818.

[33] C. Ferreira and G. Gonçalves, “Remaining useful life prediction and challenges: A literature review on the use of machine learning methods,” *J Manufacturing Systems*, vol. 63, pp. 550–562, Apr. 2022, doi: https://doi.org/10.1016/j.jmsy.2022.05.010.

[34] D. Karimanzira, T. Rauschenbach, “Deep learning based model predictive control for a reverse osmosis desalination plant,” *J Applied Math Phys*, vol. 08, no. 12, pp. 2713–2731, Jan. 2020, doi: https://doi.org/10.4236/jamp.2020.812201.

[35] A. Sircar, K. Yadav, K. Rayavarapu, N. Bist, and H. Oza, “Application of machine learning and artificial intelligence in oil and gas industry,” *Petroleum Research*, vol. 6, no. 4, Jun. 2021, doi: https://doi.org/10.1016/j.ptlrs.2021.05.009.

[36] S. I. Abba, M. Benaafi, and I. H. Aljundi, “Intelligent process optimization based on cutting-edge emotional learning for performance evaluation of NF/RO of seawater desalination plant,” *Desalination*, vol. 550, pp. 116376–116376, Mar. 2023, doi: https://doi.org/10.1016/j.desal.2023.116376.

[37] C. Fan, M. Chen, X. Wang, J. Wang, and B. Huang, “A review on data preprocessing techniques toward efficient and reliable knowledge discovery from building operational data,” *Front in Energy Research*, vol. 9, Mar. 2021, doi: https://doi.org/10.3389/fenrg.2021.652801.

[38] S. S. Ray, R. K. Verma, A. Singh, M. Ganesapillai, and Y. N. Kwon, “A holistic review on how artificial intelligence has redefined water treatment and seawater desalination processes,” *Desalination*, vol. 546, p. 116221, Jan. 2023, doi: https://doi.org/10.1016/j.desal.2022.116221.

[39] J. Jawad, A. H. Hawari, and S. Javaid Zaidi, “Artificial neural network modelling of wastewater treatment and desalination using membrane processes: A review,” *Chemical Engin J*, vol. 419, Sep. 2021, doi: https://doi.org/10.1016/j.cej.2021.129540.

[40] S. Das *et al.*, “Assessing advances in anti-fouling membranes to improve process economics and sustainability of water treatment,” *ACS EST Engg*, vol. 2, no. 11, pp. 2159–2173, Aug. 2022, doi: https://doi.org/10.1021/acsestengg.2c00184.

[41] N. Baig, S. I. Abba, J. Usman, M. Benaafi, and I. H. Aljundi, “Ensemble hybrid machine learning to simulate dye/divalent salt fractionation using a loose nanofiltration membrane,” *Environmental Science*, vol. 2, no. 10, pp. 1446–1459, Jan. 2023, doi: https://doi.org/10.1039/d3va00124e.

VITA

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